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Specifying the Content of Humble Social-Science Models

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Abstract

This paper describes ways to specify important static content of social-science models for counterterrorism without dependence on a particular computer language or environment. The ambitions are modest because the actual knowledge to be represented is limited. The premium should be on simple, clear descriptions that can be communicated, debated, and “validated” across interdisciplinary lines, rather than on pretentious detail. The approach should also lay the groundwork for exploratory analysis because of inherent uncertainties. The paper is at least a start in that direction.*

1. INTRODUCTION

Numerous researchers are building models and simulations (M&S) to be used in studies of terrorism, counterterrorism, and irregular warfare. Most are nontrivial computer programs, some embedded in complex simulation environments. Typically, they are not readily understandable and reviewable, especially for their social-science content. Reviewing computer programs is seldom easy, but it is especially hard here because most of the relevant social-science experts are not steeped in M&S methodology and technology. Policymakers are skeptical of complex M&S in this domain because they doubt underlying validity. Name-dropping developers may claim that their work reflects the theories of prominent social scientists, but considerable skepticism is warranted.

How could one do better? One possibility would be to train social scientists in the relevant mathematics and M&S, and have them become actively engaged. That is occurring in the universities with the younger generation of scientists, but the results remain complex and difficult to communicate, review, and iterate across disciplinary and functional boundaries. What else is feasible?

One answer may be to look to the long history of System Dynamics, pioneered by MIT’s Jay Forrester a half-century ago and continued by John Sterman and many others. It *has* proven possible to review System Dynamics models substantively. Some of this has been accomplished by scientists reading reports and books in which the theory

embedded in the System Dynamics models has been described. Some has been accomplished by working with the programs themselves, by sensitivity analysis, and by “counter modeling.” All of this is to be encouraged.

A complementary approach is to back away from the machinery of programming and the more arcane aspects of mathematics, and to describe the proposed model in as elementary terms as possible—in terms that allow spirited in-depth discussion in groups of social scientists and that focus attention on fundamentals without pretense of precision or certainty. It is to this second approach that the current paper contributes, albeit with respect primarily to static relationships. It builds on a good deal of experience over the last few years working with social-science colleagues at RAND and the university community. Although I personally have done considerable modeling and simulation over the decades, I believe that there is much leverage in the approach described here. In contrast, burying knowledge in *complex* computer programs seems to me counterproductive.

2. CONTRASTING APPROACHES TO REPRESENTING ANALYTIC KNOWLEDGE

One way to proceed would be to draw on the methods already used by analytically inclined social scientists. That, however, is not what I believe would be most fruitful. To understand why, it is first useful to note that anyone coming to the problem of modeling counterterrorism or irregular warfare from a background in the physical sciences, engineering, operations research, or M&S, will be struck by the disconnect between their background and the methods of the social scientists. The communication gap is wide and the ability to map knowledge between domains is difficult and treacherous.

With apologies for oversimplifying, Table 1 draws the contrast as between data-driven and theory-driven approaches, something familiar to those who have studied philosophy of science. The approaches relate to classic distinctions of inductive, deductive, and abductive reasoning, but not neatly.

Most quantitative social scientists use the data-driven approach and specialize on their own discipline’s aspects of the problem (e.g., those of sociology, economics, anthropology...). Those from a theory-driven approach tend to think in terms of systems—sometimes only “comfortable” aspects of systems that can be readily defined and measured, but sometimes more comprehensively as when they adopt the paradigms of complex adaptive systems.

* This paper greatly condenses a chapter of a book reviewing social science for counterterrorism [1-2]. The book has extensive scholarly citations that are not repeated here.

Table 1. Contrasting Approaches

Data-Driven	Theory-Driven
Specialization on one or a few factors	System approach
Focus on empirical data and theory based on readily measurable factors	Focus on factors underlying phenomena, whether or not easily measured
Statistical modeling	Causal modeling
Discussion about correlations	Causal explanations
Data-driven inquiry: "Let the data speak"	Theory-driven inquiry, with data used to test and calibrate theories

Practitioners often are deeply wedded to the approaches' philosophy. Those who are data-driven may be hostile to "theory," which they equate with mere speculation as they rattle off examples that have been nothing more than ill-considered notions (e.g., that terrorism is caused by poverty). Theory-driven scientists have in mind something very different, a unifying set of well grounded principles that make sense of a domain. Empiricists tend to insist upon using variables or factors that can be readily measured. Theory-driven scientists tend to be less demanding in that regard.

The data-driven scientists summarize knowledge with statistical concepts. Even if they use the word "explanation," it has the special meaning associated with what fraction of a data set's variance is covered by their regression model. In contrast, theory-driven scientists are deeply concerned with causality and use "explanation" in connection with reasoning through a causal chain. Although some theory-driven scientists are skeptical about causality in systems because of complex interactions such as feedbacks, their modeling is nonetheless causal, not statistical.

Attitudes about data are also interesting. To the data-driven practitioner, data is the focus. Data may allow an empirical theory to be inferred, but any such theory should be parsimonious (e.g., a simple regression using only measurable variables). In contrast, to the theory-driven practitioner, the objective is to develop an encompassing theory that pulls strands together and extrapolates well beyond what has been observed. Additional variables may be essential for understanding the phenomena, even if their values are uncertain. Data remains crucial, but for the purpose of testing and calibration. If some data is not available, the calibration may include one or more composite empirical coefficients without apology.

Many researchers fall clearly into one or the other of these "tribes," but science needs both approaches because they contribute differently as suggested by Table 2, in which the number of bullets indicates relative strength.

I have benefited from the fruits of both streams of work, so it is a matter of some passion to respect and encourage

both. Trained in twentieth-century physics and chemistry, I recall with fondness the brilliant work of scientists such as Albert Einstein and Paul Dirac, whose theories were sometimes years ahead of data—and even at apparent odds with such data as did exist. Nonetheless, data has always been crucial. The photoelectric effect and Brownian motion motivated Einstein. Spectroscopy proved the Bohr atom to be false and was crucial to development of quantum theory. So also in social science we can juxtapose the value of rational-choice theory with the insights from empirical behavioral psychology (e.g., those associated with Nobelists Daniel Kahneman and Amos Tversky). Synthesis is occurring in "behavioral economics," pioneered by Richard Thaler among others.

Although both data-driven and theory-driven approaches are crucial, it seems clear that extant work on the "analytic" side of the relevant social sciences is overly dominated by the statistical approach and that much more work is needed in causal system modeling. The rest of the paper focuses accordingly. Ironically, the best insights to guide that work often come from social scientists whose products are purely in prose—prose with the intellectual structure needed for causal modeling. An important exception is that econometricians, despite their empiricism, work creatively to infer causality.

The remainder of this paper addresses methods for representing social-science causal-system knowledge in simple and transparent fashion.

Table 2. Relative Strengths

Issue	Data-Driven (Atheoretical)	Theory - Driven
Cautions	••••	
Empirical disconfirmation	••••	
Explaining phenomena simply	••••	
Predictions where theory is lacking	••••	
Disconfirmations based on deeper settled theory		••••
Predictions for new situations		••••
Tightening and calibrating a model		••••
Clarifying underlying mechanisms		••••
Causal reasoning		••••

3. PRINCIPLES

A first principle of the suggested theory-oriented approach is to reject the search for simplistic conclusions such as "It's all about X" (for example, "terrorism is all about

poverty” or “It’s all about radical Islam”). In fact, *numerous* factors contribute to phenomena such as terrorism. A second principle is to strive for understandability. Decision makers need analysis based on causal models allowing them to reason about the phenomena, including effects of multiple factors, potential interventions, changes of circumstance, or changes in the system itself. Such analysis should lend itself to encapsulation in a “story.” It should integrate separate streams of knowledge. This is recognized in the pleas of national governments for what is variously referred to as a “comprehensive” or “whole-of-government” approach. This is in contrast to the more parochial scholarly literatures.

How does one go about describing complicated systems? Methods certainly exist. System engineers have methods for dealing with exceedingly complicated projects. Systems Dynamics has been used in a wide range of policy applications, including representing the concepts of the recent U.S. Army/Marines counterinsurgency manual. My own work on strategic planning and analysis uses decomposition, multiresolution modeling, exploratory analysis, and the highlighting of critical system components. It then draws implications for portfolio-style investments [3-5].

Some crucial distinctions should be noted. In classic system engineering the components can be comprehensively and precisely defined; interactions can be specified, and work can proceed in parallel on the components. In problem domains such as irregular warfare that revolve around humans, matters are not so straightforward. The natural modules may not all be recognized, may change with context, and may have subtle interactions. Model composition is much more difficult than normal software engineering. The system may be dynamic, even “organic.” Technically, there is a need for “variable-structure modeling.” This may be unsettling to those with a desire for neatness and stability, but it comes more naturally to those familiar with the realities of human behavior, networking, and complex adaptive systems generally. It follows that there are many lessons to be drawn from past work but that describing social-science knowledge poses special challenges.

Some key features of the approach that I will sketch are (1) qualitative modeling; (2) relating variables (factors) to each other; (3) depicting the combining logic of multifactor interactions, including feedbacks and non monotonicities; (4) dealing with uncertainty (including random effects); and (5) dealing with dynamics such as learning and adaptation. Let us address them in turn.

3.1. Qualitative Modeling

The best way to express social-science knowledge is often with qualitative modeling—not as a poor second choice tolerated by necessity but because qualitative factors are often natural. This means accepting soft and squishy variables; to ignore them would be as foolish as ignoring the effects of an organization’s morale or the optimism of a

population about the future economy. Much of the counterterrorism (CT) subject area is about such soft factors, as is evident in the social science coming from historians, anthropologists, sociologists, and psychologists.

Qualitative variables may be given a degree of rigor—for example, by assigning them discrete values such as in the set Low, Marginal, High and by then describing the circumstances in which the different values apply. To avoid circularity, the distinctions drawn must be observable in principle, even if observations are rare (as when intelligence uncovers secret documents). Over time, the values of such qualitative variables can be more precisely defined.

In the spirit of causal system modeling I believe that we should focus on the purest elements of the phenomena in question, rather than thinking in terms of dubious proxies that may be more easily measured. For example, a region’s level of democratization is not well captured by data on whether elections occur. We cannot avoid using surrogate measures to test our knowledge empirically, but we can defer doing so as long as possible so as to focus on the deeper concepts.

3.2. Specifying how Factors Relate

Many factors affect CT phenomena. How can their relationships be represented comprehensibly? As an effective “baby step,” I have used “simple factor trees,” as illustrated in Figure 1. If a subject’s disciplinary experts identify an alphabet soup of relevant factors, say A, B, . . . Z, then the hope is to identify relationships among those factors in an overall causal structure as shown: with only a few independent high-level factors mattering, but with those dependent on lower-level factors. In Figure 1, A, K, and P are independent from a structural perspective (their values may be correlated). In contrast, R has some effect on P as well as on K (the dashed line indicates a weak effect). Similarly, N affects both D and R. The result is a “nearly” hierarchical decomposition (weak interactions exist among branches indicated with dashed lines). Such simple depictions can sometimes make relative order out of chaos.

The factor-tree method draws on past work. The ubiquity of “nearly hierarchical decomposition” was described long ago by the late Nobelist Herbert Simon. Multiresolution modeling [4] using *approximate* abstractions is useful in both “hard” applications and soft applications such as building behavioral models of adversaries [6]. It organizes knowledge much as intelligent people do in making sense of complexity.

Some readers will perhaps notice that graphical depictions such as Figure 1 are variants of the *influence diagrams* of System Dynamics in which if two variables are connected by an arrow, it means that an increase in the first variable (at the arrow’s tail) will tend to increase the second variable (at the arrow’s head). A negative sign on top of an arrow, as between B and A, indicates that the effect is reversed—that an increase in the first variable tends to decrease the second. The variables, or factors, are usually thought of as having “levels” (for example, the degree of a

population's discontent or of an individual's religious ardor). Many variants of such diagrams exist, only some of them in System Dynamics narrowly. Many people in policy analysis, for example, prefer to use the *Analytica*® modeling system, as do I. In fields using Bayesian belief nets, "influence diagrams" mean something a bit different, although related. For expository purposes, my own diagrams may include dashed lines to indicate a weak effect, as in Figure 1, or thicker lines to indicate a stronger effect (e.g., factor K's effects in this figure). This modest extension of influence-diagram notation has proven useful in research, collaboration, and discussion with senior officials.

The simple factor-tree version suppresses the complexities of dynamics and feedback, omits showing most of the many weak cross-branch interactions that obscure seeing forests, and omits the "bubbles" common in modeling and programming diagrams. It is a bare-bones static representation of important relationships—i.e., a good starting point for much discussion, but it is a "baby step."

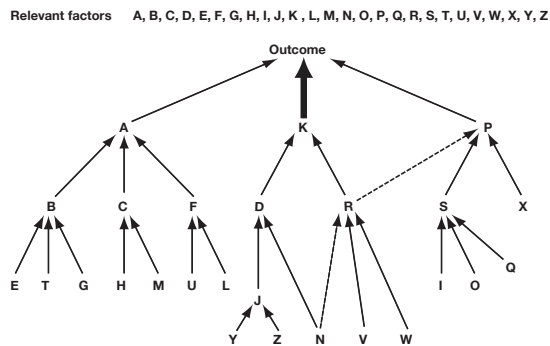


Figure 1: Nearly Hierarchical Decomposition

3.3. Representing Combining Logic of Multi-Factor Interactions

Such simple factor-tree diagrams describe what factors operate together and affect others, but they do not say *how*. Do the factors have independent effects or do they interact? Are the effects direct or indirect? Is there some order in which they must arise? Figure 2 illustrates how some of these issues can be represented graphically. It illustrates what I call a combining logic diagram (CLD) or a "factor tree" (as distinct from a "simple" factor tree).

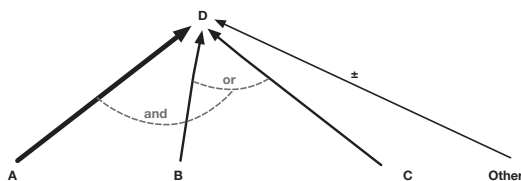


Figure 2: A Combining-Logic Diagram

A CLD has a second baby step: it includes some "and / or" notation to a factor-tree version of an influence diagram, implicitly assuming binary values such as yes or no (or true and false). The figure indicates that B and C are substitutable for each other but that factor A has independent importance. According to Figure 2, a positive outcome (yes) is more likely to occur if A and (either B or C) is yes (i.e., true). Ignoring the "Other" factor temporarily, this means that—to a first approximation—A is a necessary condition, whereas B and C are alternative conditions. The assumption of binary values is crude but useful, as illustrated in artificial-intelligence texts and in social-science work by Charles Ragin. Fine-tuning can be deferred to model builders, who need more precision. Such a cavalier attitude would be inappropriate in a more exact science, but the baseline of social-science theory is arguably confusion calling out for sense-making, even if approximate. Based on experiences in perhaps a score of recent briefings about our recent work [1], my colleague Kim Cragin and I have found that such depictions can greatly enhance communication in a sizable group of people. Even people who claim not to like diagrams can grasp them quickly, after some initial resistance.

Other simple graphics can be used to convey additional crucial features of how variables interact, e.g.: (1) monotonicity versus, say, an inverted-U dependence of one variable on another; (2) feedback loops; (3) the simplification of feedback-loop phenomena that can occur when one coarse-grains over time, and (4) assumptions about thresholds and ceilings. All such depictions are additional baby steps.

Commenting briefly on just the last of these, consider the importance of such nonlinear effects as thresholds. Human beings may utterly ignore risks, for example, until they reach some level of apparent significance. This may help explain historical incidents of "unreasonable" risk-taking, such as that of Saddam Hussein in 1990-1991 and then in 2003. At the same time, many effects have a saturation point.

There is special value in treating thresholds and ceilings in the modeling of counterterrorism because they may play a role in *theories of victory*. It is probably unnecessary to reduce materiel and human-capability components of a terrorist group to zero before effectiveness drops to negligible proportions: We may reasonably hope to see critical-mass effects, to see terrorist organizations collapsing rather than degrading continuously. Unless such matters are represented analytically, we could greatly underestimate the value disrupting an organization by targeting its leaders or forcing it to change operational locations and processes frequently.

It is easy to represent the essence of such nonlinear phenomena with simple viewgraphs that can be understood and debated. To implement them, of course, one can use and tune simple mathematical functions such as the sigmoid, but

such details are not crucial to discussion among subject-matter experts.

3.4. Randomness and the Need for Humility

Even if we have done a good job identifying factors and combining relationships, social phenomena will often yield surprises. This may be the consequence of “hidden variables,” which might not be knowable in advance. Such variables include the health and mood of protagonists, perceptions about exogenous events in the world, and the order of events. As a practical matter, many phenomena have a random component.

How should randomness be handled? The first principle is humility: We should aspire to estimating the *odds* of being correct rather than making confident predictions. Analytically, we can add explicit random variables just to remind us constantly of uncertainty, which can work either positively or negatively [7]. Alternative important approaches, not discussed in this paper, involve Bayesian nets or influence nets, methods for which have evolved substantially over the last decade or so.

Figure 2 illustrates representation of the randomness issue with the variable labeled “Other” and the ambiguity of the sign on the arrow. The heaviness of the arrows indicates that A is especially important, that B and C are less so, and hidden variables even less so. Much can be conveyed with diagrams with only this level of complexity.

3.5. Competition, Learning, and Adaptation

Competition, learning, and adaptation are crucial in social phenomena, but representing them is not always easy. Competition can sometimes be represented by game-theoretic methods. In the simplest form, these do not purport to describe the actual dynamics of interaction but rather to show what outcomes would be like if competitors act most effectively in their own interest. This can be done sequentially, as in a prototype CT model developed by my colleague Richard Hillestad and in work of Elizabeth Paté Cornell at Stanford, and by Alex Levi and Lee Wagenhals at George Mason. Modern game theory includes cooperation and competition and can include agent-based modeling, as discussed below.

Agent-based modeling (ABM) is closely associated with the study of complex adaptive systems (CAS) generally. ABM can be included in any of a number of simulation environments, such as REPAST, SEAS and COMPOEX.

As I have described elsewhere, it may not be fruitful in policy work to follow the dynamics of complex adaptive systems to see the details of precisely how emergent phenomena such as insurgencies arise. Such details may instead be left for separate research, with the fruits of the research being reflected in simpler models identifying when situations should be expected to be unstable. In any case, connecting the worlds of micromodels and macromodels is both exciting and challenging.

Some researchers believe that detailed agent-based simulations can be used predicatively. They sometimes disparage the feasibility of social-science modeling that does not include agent-based modeling. Such researchers have far more faith in the validity of the current ABMs than I do and far less confidence that the consequences of the various “emergent phenomena” can be represented macroscopically. It is an interesting theoretical debate that will be resolved over time with experience.

Other classes of model may also be important, such as models describing the consequences of a conservation law or of aspects of a system that are constant after a steady state has been reached. Some of these types are familiar in the physical sciences, economics, and other social-science disciplines. I mention them because the common use of computer simulations sometimes crowds out simpler depictions.

3.6. More Specification

There are limits to what can be expressed diagrammatically without excessive complication. The next step, arguably, is to use simple outcome tables.* Table 3 is intended to reflect more precisely the same thinking as in Figure 2. Factor A is especially important; if it is Low, then the claim is that outcome D will be Low. If factor A is High, then outcome D will *probably* be High if at least one of B and C are High, and *very likely* be High if both are High. A modeler familiar with expert judgments could give these a bit more precision, such as associating “moderate” with ~ 60 percent and “high” with ~80 percent in probability terms, or odds of, say, 3:2 and 4:1. Subject-matter experts could ponder about whether those would be “about right.”

The continuing point is that simple representations of knowledge may have a degree of imprecision consistent with the knowledge itself. Even if the factors must be allowed more discrete values (say three, as in Low, Marginal, High), my experience in developing artificial-intelligence models using highly structured rules demonstrates that sophisticated but comprehensible models can be built using these table-driven techniques developed for the RAND-Abel language by colleagues Ed Hall and Norman Shapiro [8,9]. With straightforward mathematical techniques and appropriate spot-checking by human experts, much can also be done to verify and even validate—relative to subjective expert knowledge.

The logic table (Table 3) is equivalent to the mathematics, described in pseudo code as:

```
If A is High and (B is High and C is High)
Then: D is High; Confidence is High
Else
```

* It is unnecessary to employ the formalisms or sophistication of fuzzy logic, although some will see such tables in fuzzy-logic terms.

If A is High and (B is High or C is High)
 Then: D is High; Confidence is Moderate
 Else: D is Low; Confidence is High.

In this case, the pseudo-code is as good as or better than the table, but communication is usually better with table structures. As dimensionality increases, the length of pseudo code or equivalent tables can be greatly reduced by exploiting operators such as \leq and a value of “don’t care” as used in the RAND-ABEL language [8-9] or tables in prose [2].

Table 3: A Simple Outcome Table

A	B	C	D	Confidence
High	High	High	High	High
High	High	Low	High	Moderate
High	Low	High	High	Moderate
High	Low	Low	Low	High
Low	High	High	Low	High
Low	High	Low	Low	High
Low	Low	High	Low	High
Low	Low	Low	Low	High

4. A VISION OF ANALYSIS AMIDST UNCERTAINTY

The preceding sections have emphasized the special difficulties associated with representing uncertainty and soft, qualitative knowledge as occurs in social science. A subsequent question is what this means for *analysis*. The primary implication is that

The objective of analysis in social science should often not be reliable “prediction,” but rather an understanding of possibilities and perhaps of rough probabilities or odds.

This admonition applies to much policy analysis generally, but certainly to defense planning. The U.S. Department of Defense has come increasingly to recognize that massive uncertainty exists about such fundamental issues as who will be the future adversaries of the United States, where and under what circumstances future wars will occur, and what strategies and tactics will be employed. The result has been an emphasis on capabilities-based planning [3] in defense and related domains such as homeland security.

The philosophy reflected in these efforts is to seek what I have long called “FAR strategies,” i.e., strategies that are Flexible (suitable for different missions), Adaptive (able to deal with different circumstances as they arise), and Robust (resilient to shocks). Regrettably perhaps, various authors (including myself) sometimes lapse into shorthand using terms like “planning for adaptiveness”, “robust-adaptive planning,” or “planning for agility” to mean planning that addresses all of the FAR dimensions. All of these applications relate to people and organizations, that is, to social phenomena.

A key element of achieving FARness in strategy is *exploratory analysis* as illustrated in Figure 3. Consider first the flow along the top of the figure. Given some alternative packages of strategies, tactics, and investments, which we

can call Options 1, 2, 3, and 4, we seek to assess them despite extraordinary uncertainty about “everything” (see the assumption classes at the bottom of the figure). To do this, we develop an experimental plan that systematically varies the assumptions—even assumptions about the functional form of the model being used for evaluation! The experimental plan then drives computational experiments. In each experiment, the model (an “engine” for generating cases) has a set of inputs and produces outputs (which may be stochastic). The plan may call for huge numbers of runs, but actually conducting the runs is a mechanical matter behind the scenes. The results can be analyzed like “data” to see if patterns emerge. The results can be integrated and summarized for comprehensible displays such as the colored scorecards used in RAND’s approach to portfolio analysis (bottom right) [3,5]. Analysts examine the results in a myriad of ways using such methods as standard statistical regressions, motivated metamodels, and data mining [7]

This “exploratory analysis” approach represents a very different paradigm than starting with a baseline scenario, simulating the consequences for a few alternative strategies, and then conducting a handful of excursions. It is an evolution of RAND methods developed over many years by me, Steven Bankes, Robert Lempert, and many colleagues. A core concept is recognizing the need to assess capabilities across a broad, parameterized n-dimensional scenario space.

Some traditional analysts view such an image with horror because they are used to spending months working out details of a baseline model and database. Fortunately, since the premium is on achieving a coarse synoptic view, simple models often suffice in which case running huge numbers of cases may be relatively straightforward, occurring behind the scenes. The fruits of exploratory analysis can be shown in displays that identify the circumstances in which outcomes are favorable or unfavorable, and where the boundary lines lie, that is, defining different *regions*. I show an example late in the paper. The intellectual content has to do with learning how many importantly different regions exist and where they lie in n-dimensional space.

In some cases, the regions can be identified by clever analysts without much computation, in which case it is even easier to identify a small approximate “spanning set” of analytical cases, one or two for each important region [5]. In assessing alternative courses of action, it is then necessary to test only against the spanning-set cases because they “stress” the alternative in all of the most important ways. Under budget pressures, policymakers could decide to deemphasize some of the case, but they would do so with recognition of the risks.

Once the synoptic view has been accomplished with low-resolution exploratory analysis, detail can be added selectively to better understand implications. This process is most compelling and rigorous when combined with multiresolution modeling.

This vision is ambitious, but 15–20 years of experience now exists with exploratory analysis, which has proven its viability and usefulness. Our experience also demonstrates that uncertainty and data gaps need not be paralyzing.

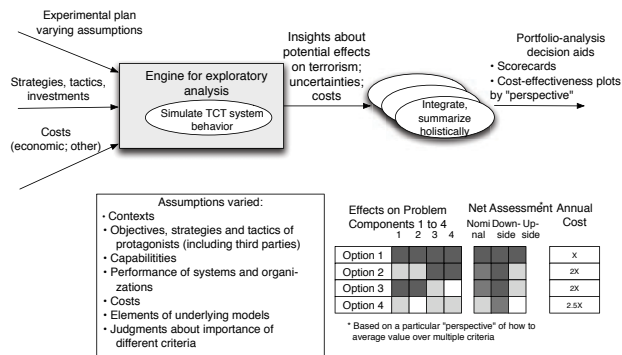


Figure 3: The Vision of Analysis

4.0 Illustrative Application

The previous sections have described generic methods for communicating social-science knowledge. What follows illustrates how they can be used.

My own work on counterterrorism began in collaboration with terrorism scholar Brian Jenkins in a monograph intended for policy makers but suggesting a “system” view [10]. Companion papers in the larger study from which this paper draws [1] reviewed the social-science literature on terrorism and counterterrorism with regard to root causes (Darcy Noricks) [11], individual radicalization (Todd Helmus)[12], achieving and maintaining public support (Christopher Paul)[13], and how terrorists and terrorist organizations make decisions (Brian Jackson)[14]. Each included a factor tree relating the factors identified in the respective reviews. For the purpose of this paper, however, let me show only a single tree, which was informed by the others as well as my own past work. Figure 4 shows a depiction of the propensity to participate in or actively support terrorism, expressing it as a function of four primary factors:

- attractiveness of and identification with a cause or other action
- perceived legitimacy of terrorism
- acceptability of costs and risks
- presence of radicalizing or mobilizing groups.

The first of these is my renaming in “positive terms” the factor related to motivation, which is often expressed by

authors in terms of anger, frustration, and the like. As has been repeatedly noted by terrorism scholars such as Brian Jenkins, Mark Sageman, and Dipak Gupta, terrorists do not see themselves as “terrorists.” They often see themselves as warrior heroes supporting either a cause (religious or otherwise) or, at least, an activity that they find exciting. The second factor uses the term “legitimacy/acceptability.” As we know from accounts of terrorists’ internal debates, such matters are important—even if the terrorists conveniently discover rationales for doing what they are motivated to do anyway. The third factor, acceptability of costs and risks, is implicit in some papers and explicit in others. The fourth factor is often discussed as a separate subject but has top-level significance. Note also, at the bottom, that charismatic, entrepreneurial leaders can be very important, something not always acknowledged by scholars.

All the factors at the bottom affect susceptibility to the more specific factors indicated in the tree. At the second and third levels of detail, Figure 4 shows more than a dozen constituent factors. All of these are discussed in one form or another in my colleagues’ review papers. The papers offer different perspectives as to how they come into play, but the differences are arguably not of first-order importance.

As discussed above, “ands” and “ors” are important in Figure 4. To first order, the research base suggests that all of the top-level factors must surpass some threshold or terrorism will decline. However, there are different ways that a cause may be seen as attractive and that terrorism can be seen to be legitimate. Similarly, a number of factors affect the “negatives,” that is, determine the perception of costs and risks.

Although only one of several possible high-level perspectives, the figure highlights overarching factors that appear repeatedly in the research literature. Further, it does so holistically rather than asserting, for example, that participation in or support of terrorism is *just* a consequence of a cost-benefit calculation or that the current wave of terrorism is supported by popular sympathy driven *only* by Salafism or only by political grievances. To put matters otherwise, the intent of the diagram is to cover all of the available respectable explanations, not just the one deemed currently by some particular experts to be dominant in a particular time and place. Any contributor to the relevant scholarly literature should be able to find his work on the tree.

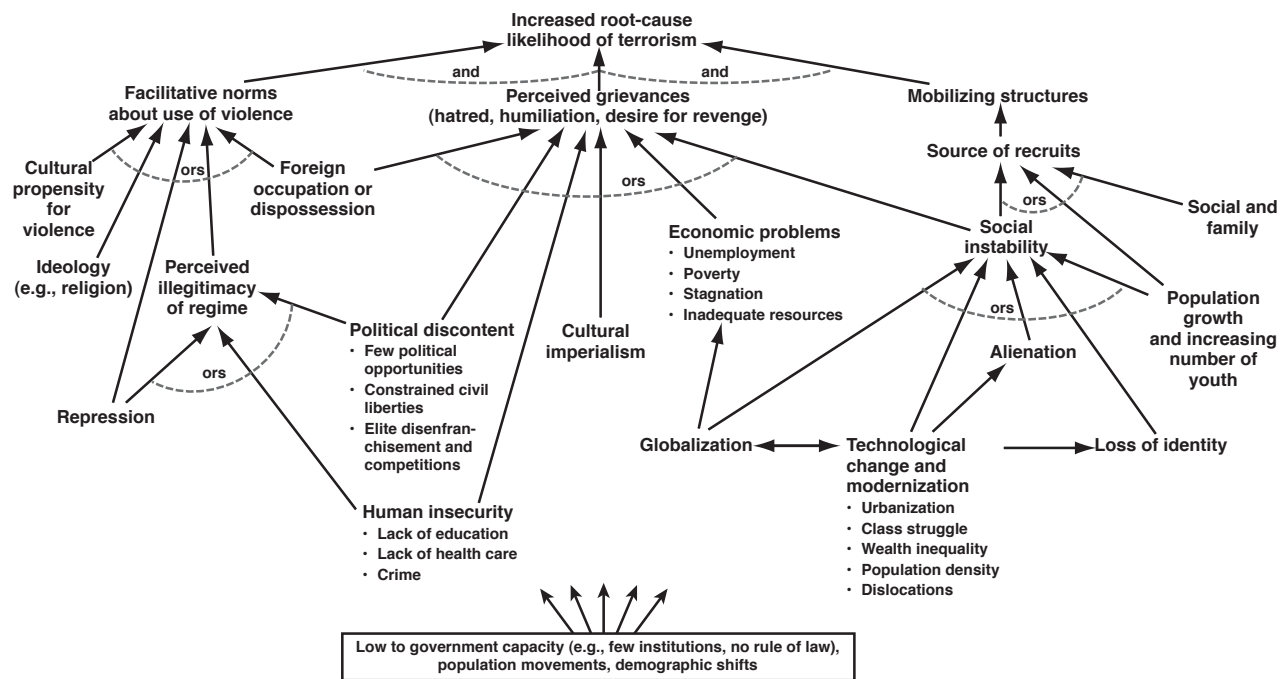


Figure 4: A Fault Tree for Support of Terrorism

At first glance, it may appear that the factors of Figure 4 are assumed to combine via rational choice: Is there value to the terrorism, is it legitimate, are the costs and risks acceptable, and is there a mechanism? As discussed in a paper by colleague Claude Berrebi paper [15], much empirical data can be understood with the rational-choice model. That model *is* very useful.

Social science tells us, however, that that model is often not descriptive. The more general concept is arguably *limited rationality*. People attempt to be rational, that is, to take actions consistent with their objectives, but they are affected by many other influences that my colleagues and I discussed in a review study [16] drawing on work of Nobelists Simon and Kahneman, as well as researchers concerned with intuitive decisionmaking such as Gary Klein and Gerd Gigerenzer. The key influences are

1. the constraints of *bounded rationality*, which include erroneous perceptions, inadequate information, and the inability to make the complex calculations under uncertainty demanded by strict “rational choice”; the result is often heuristic decisionmaking, which employs simplified reasoning and may even accept the first solution that appears satisfactory
2. the consequences of *cognitive biases*, such as the tendency to demonize opponents, to select information that bolsters what one wants to believe, to ignore risks below a threshold of apparent likelihood, and to make

use of information that is most readily “available” cognitively (for example, the most recent report)

3. the related positive and negative consequences of *naturalistic decision making*, which is more intuitive and dependent on situation-dependent heuristics than evaluation of alternatives.

In still other cases, behavior can scarcely be called rational; it is driven by emotions (whether fervor for action or vengeance on the one hand or unreasonable fear on the other) and is strongly affected by events and social context (as when an unhappy crowd turns into a rioting mob). Figure 4 is agnostic about such matters. The acceptability of costs and risks, in particular, could be determined by a rational calculation, heuristics, cognitive biases, or emotions at the time.

To be sure, Figure 4 is simplified. First, it glosses over level-of-analysis issues; second, it treats many important issues as features of the surrounding context (see the boxes at the bottom, which refer to topics discussed in the cited papers). Third, it is intended as a first approximation, recognizing that any such depiction will have some counterfactuals, which is why the individual papers cited include numerous cautions. Finally, as mentioned above, it suppresses many weaker interactions, inclusion of which would muddy everything. Nonetheless, it is very useful.

The next question might be how knowledge about participation in or support for terrorism connects to the incidence of terrorism generally. For this, it is useful to

think in terms of a system-level influence diagram (Figure 5). In this diagram, the terrorist organization already exists, but its operational capabilities (central oval) may increase or decrease as a function of the resources and organizational structures available to it, which in turn depend on support obtained from states (for example, Iranian support for Hezbollah), general populations (for example, broad popular sentiment support for al-Qaeda), or more specific popular support (support of expatriate communities in western Europe for al-Qaeda or local affiliates). All of the nodes, of course, have subcomponents, and it is by no means straightforward to know how they aggregate to generate the top-level effect. A virtue of multiresolution modeling is that where aggregate-level knowledge is better than microscopic knowledge, it can be used directly.

Given a degree of operational capability, the terrorist organization has the potential to conduct attacks, but the potential effects depend also on the targets' vulnerabilities. If support for action is strong enough, and if operational capability is adequate, then attacks will ensue. Those will have effects, which in turn will affect subsequent support. Another spectacular event akin to the attacks on the U.S. World Trade Center and the Pentagon might increase support for what would be seen as a revitalized al-Qaeda. Or it might spark back-reaction because of the loss of human life and retaliation. Or both. The consequences, then, might have positive or negative feedback effects (hence the +/- symbology).

The primary function of Figure 5 is to illustrate how support for terrorism matters. Support, however, comes in many different forms. Suppose that we put aside state support, which is a subject unto itself, and consider only public support. That also varies markedly. Support may be so great that individuals will actually become terrorists; or it may come in the form of active or passive public support without direct participation in terrorism attacks. Such public support is widely regarded in social science as a key to the success or decline of terrorism.

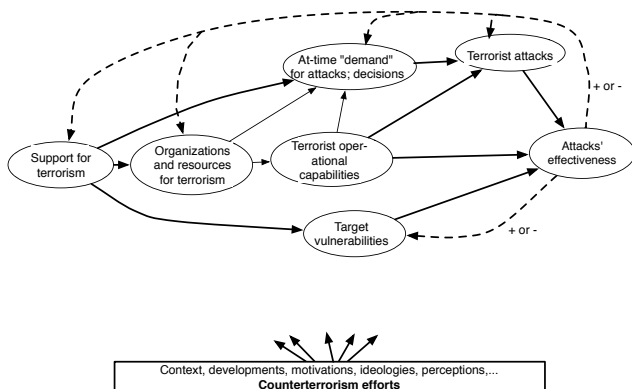


Figure 5: A System Diagram Relating to Terrorism

If Figure 5 were correct, and if it could be used as the basis for a more extensive exploratory analysis, one result might be the kind of diagram shown in Figure 6. This “region chart” shows the expected propensity to participate in or actively support terrorism (represented by color) as a function of the attractiveness of and identification with cause (abbreviated as “motivation” along the vertical axis), the price (acceptability of cost and risk along the horizontal axis), and the perceived legitimacy (left versus right panel). Radicalizing groups are assumed to exist in this example.

The notional plot asserts that if motivation and a sense of legitimacy are high enough, support for terrorism is likely to be high (dark) (for example, the top right in either panel). However, if the sense of legitimacy is reduced (such as by the terrorists killing too many of the wrong people or by continuing to kill despite political and social progress within the relevant community), then the level of support will be much less, given the same motivation and sense of price (right panel). The notional plot suggests that the perceived-legitimacy factor has high leverage. For point A, for example, moving into the desirable regime of low support would require much less in terms of raising perceived price or reducing motivation if legitimacy were deemed low (right panel versus left).

Counterterrorism, then, should seek to reduce motivations, to increase the sense of *illegitimacy*, and to impose increasing costs on those who participate or support. Disrupting the organizations for radicalization and mobilization would also have great value (not shown). The purpose here is not to provide some new revelation (after all, the conclusion should resonate with many readers' past knowledge), but to illustrate how knowledge and model-based work can be expressed analytically in terms understandable to people who haven't done the modeling or computations.

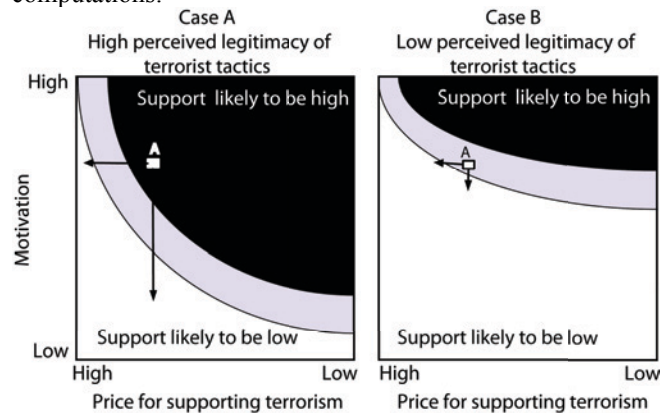


Figure 6: A Notional “Region Plot”

5. CONCLUSIONS

Ultimately, this paper is an integrative, theory-oriented think piece that suggests major features of an approach to representing knowledge and conceiving analysis. It has illustrated how factor-tree methods of decomposition can be

used to modularize problems so that they can be addressed separately but seen as part of a whole. The vision of the “whole,” of course, depends on the perspective taken. That is, *which* representation one uses depends on the challenge being addressed, such as “understanding the terrorist phenomenon” versus laying out a counterterrorism campaign and allocating resources wisely. In the longer paper from which this is drawn my colleague Kim Cragin and I recommend procedural next steps for improving the analytic basis for social-science modeling. This should include module-by-module discussion, iteration, and “validation” of knowledge using techniques such as the fault trees and outcome tables discussed earlier. Further, it may benefit from work with very simple computer models accessible to “anyone,” such as Analytica models that I have used for such purposes. Such models may be used to generate visuals for review and iteration by groups. Once the core knowledge is agreed, it could be reprogrammed in any of many environments. Such work is now underway.

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Biography

Paul K. Davis is a Principal Researcher at the RAND Corporation and a Professor of Policy Analysis in the Pardee RAND Graduate School. He has authored well over a hundred interdisciplinary books and papers on strategic planning and analysis (primarily in defense); advanced analytic methods such as multiresolution modeling, exploratory analysis under uncertainty, and portfolio analysis; large-scale wargaming and simulation; and reflecting modern decision science in methods intended to support senior policymakers. Most recently, he co-edited a major RAND book on social science for counterterrorism. Dr. Davis has a B.S. from the University of Michigan and a Ph.D. in chemical physics from M.I.T. He has served on numerous panels of the U.S. National Academy of Sciences and Defense Science Board.